Estimating Heterogeneity in Lifetime Earnings Risk*

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Abstract

This paper measures risk in the present value of workers' remaining lifetime earnings. Building upon a common earnings specification, our estimate combines flexible, heterogeneous forecasts of individuals' expected earnings growth rates and the variances of potential permanent and temporary annual earnings shocks throughout their future careers. This measure of lifetime risk is only moderately correlated with those annual risks and is a much stronger predictor of several major life decisions. Unlike annual risk, it is often larger for relatively affluent groups. It also has many other covariates, including occupations and industries, and it has risen steadily since 1970. **JEL codes:** D81, D15, J31.

1 Introduction

Despite the pervasive influence of life-cycle models over the last six decades (Modigliani and Brumberg 1954, Friedman 1957), most empirical analyses of responses to income risk are based on annual rather than lifetime measures of risk. While annual measures may be more appropriate in applications in which temporary income shocks are important—such as when there are significant credit constraints or fears of insolvency—in other applications they are likely an inferior substitute

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for longer-term measures, perhaps especially when choices involve long-term commitments that would be costly or impossible to reverse (e.g., home ownership, fertility, or marriage). A heterogeneous, comprehensive measure of lifetime earnings risk could thus help to investigate how agents' choices respond both to the risk itself and to other factors correlated with it.

This paper thus aims to measure the risk in the present values of workers' earnings over their remaining careers and to identify its covariates. We emphasize risk from earnings because they comprise the bulk of most workers' lifetime budgets and are subject to uninsurable risk. Our empirical approach builds upon a canonical model of earnings dynamics that includes both permanent and temporary shocks to workers' annual earnings. The model yields expressions for the mean and variance of their remaining lifetime earnings, both of which are functions of their annual risks in each future year. We estimate those annual risks via a modest variation on Meghir and Pistaferri's (2004) method that allows for greater heterogeneity, then use them to compute the lifetime expressions. Since our ultimate goal is to measure responses to risk, our primary task is to capture risk arising from all channels, and we do not attempt or claim to identify its causes. In keeping with those priorities, we use specifications that permit forecasts to vary flexibly with workers' personal and job characteristics, over the life-cycle, and across forecasting horizons (e.g., because workers may not be as certain about their jobs in the more distant future), with estimates based on observed experiences of similarly-situated workers rather than on strong functional form assumptions. The analysis also yields some ancillary evidence on the share of workers' lifetime budgets that are comprised of their expected future earnings (i.e., exposed to lifetime risk).

We know of only two previous studies that report explicit estimates of lifetime earnings risk, Koerselman and Uusitalo's (2014) analysis of risk-return trade-offs in human capital investments in Finland and Dillon's (2018) investigation of the extent to which job mobility provides insurance against productivity shocks. While both papers address their own topics quite admirably, neither is ideal for our goals: due to the context, the former measures risk only at the start of workers' careers and thus reveals little about risk faced by older workers or heterogeneity beyond its immediate topic, while the latter would miss variation not caused by the modelled mechanisms. A somewhat

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larger literature computes disaggregated estimates of annual earnings risk (Meghir and Pistaferri 2004, Sabelhaus and Song 2009, Jensen and Shore 2015), and others have used them to study precautionary savings (Carroll and Samwick 1997), human capital investments (Saks and Shore 2005), and family structure (Drewianka 2010, Santos and Weiss 2016, Sommer 2016). However, we show that annual earnings risk is often a poor proxy for lifetime risk.

For one thing, annual and lifetime measures of risk are often not strongly correlated. The divergence owes in part to variation in workers' career horizons and expected earnings growth, but the distinction between temporary and permanent annual shocks plays an important role as well. While we find that temporary shocks tend to be significantly larger, the risk of permanent shocks accounts for a much greater share of lifetime earnings risk. This is not surprising, and it is even reassuring for the goal of measuring lifetime risk because measurement error in the earnings data (Duncan et al 1985) likely creates an upward bias in measures of temporary (but not permanent) annual risk. Even so, workers' current risk of annual earnings shocks is still an imperfect measure of their lifetime earnings risk, both because it tends to decrease over the life-cycle and because the workers should anticipate that their risk may change in the future, e.g., if they change jobs.

The significance of the annual-lifetime distinction is illustrated by a validation exercise presented at the end of the paper that shows several major choices (e.g., whether to buy a house) are more sensitive to our measures of lifetime risk than they are to measures of annual risk. Besides demonstrating the pitfalls of using annual risk in lieu of lifetime risk, these results also lend credibility to our estimates, as there would be no reason for decisions to co-vary with an irrelevant or poorly measured variable. Indeed, the estimates are consistent with large behavioral responses to lifetime earnings risk, often comparable in magnitude to those of expected lifetime earnings itself.

Consistent with the evidence on annual permanent earnings shocks, our results indicate lifetime risk decreases over the life cycle, but has risen over time and across birth cohorts. We also identify several covariates of lifetime risk, including occupations and industries. While these are not necessarily causal relationships, the correlations imply that estimates of those other variables' effects on behavior may be biased if we do not control for risk. More optimistically, the variation

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across occupations and industries is encouraging because it may be reasonable to assume they affect workers' choices only via the earnings process (Carroll and Samwick 1998), making them a promising source of independent variation for causal analyses.

One other striking finding is that lifetime risk is relatively high for many affluent groups like college graduates, professionals, and Whites and Asians. In contrast, many groups with below-average incomes have high levels of annual earnings risk but modest levels of lifetime risk, e.g., agriculture and construction workers, Blacks and Hispanics, those with health limitations. While the comparison is easily understood – the latter groups are more apt to report large temporary earnings fluctuations that contribute little to lifetime risk – it provides a stark example of the distinction between the two concepts of risk and the dissimilar financial challenges facing various populations.

The next section presents the model of earnings dynamics and shows how to combine its parameters to measure lifetime earnings risk. Section 3 explains how we estimate those parameters, Section 4 describes the data, and Section 5 discusses some notable intermediate results. The main results on lifetime earnings risk appear in Section 6. Section 7 provides a concluding discussion. An Appendix provides details about the specifications used to implement the empirical strategy and discusses the results' robustness to some alternatives.

2 Lifetime Earnings Risk: Theory

2.1 Definitions and Concepts

Consider an agent choosing control κ to maximize the expected value of objective $H(Z, \kappa)$ subject to uncertain lifetime budget $Z \equiv W + V$. Part of Z is the agent's current wealth W, which need not be subject to risk if riskless assets are available. The rest is the present value of future earnings $V = \int_0^T e^{-rt} y(t)\, dt$, where $y(t)$ is the agent's earnings t years from now and r is the discount rate. This is uninsurably risky, so define expected value EV, variance $\operatorname{Var} V$, and coefficient of variation $c = (\operatorname{Var} V)^{1/2} / EV$. Let $\theta \equiv EV/EZ$ be the share of expected Z subject to risk.

Kimball (1990) shows how the optimal choice $\kappa^*(Z)$ can be approximated using moments of

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V. Defining $\rho^* \equiv -(H_{KZZ}/H_{KZ}) \cdot (EZ)$, his result implies

$$\kappa^*(Z) \approx \kappa^* \left[EZ - \frac{1}{2}\rho^*\theta c^2 EV\right] = \kappa^* \left[EV\left(\frac{1}{\theta}\right)\left(1 - \frac{1}{2}\rho^*\theta^2 c^2\right)\right] \tag{1}$$

Thus, a log-linear model of κ^* ($\kappa^* = \widetilde{\beta_0} + \beta_1 \log Z$) could be Taylor-approximated

$$\kappa^* \approx \beta_0 + \beta_1 \log EV + \beta_2\theta + \beta_3 c^2. \tag{2}$$

These functional forms are one reason we use c^2 as our measure of lifetime risk. Its ratio form also makes c^2 much less sensitive to the discount rate than are EV and $\operatorname{Var} V$ separately, and it removes complications due to temporary earnings shocks $\nu(0)$ that occur at the time of the forecast. In the model below, inability to identify $\nu(0)$ means we can only estimate EV and $(\operatorname{Var} V)^{1/2}$ up to a factor $\exp \nu(0)$, yet we can still compute $c^2 = [\operatorname{Var} V \cdot \exp[2\nu(0)]] \;/\; [EV \cdot \exp \nu(0)]^2$.

2.2 Constructing Lifetime Risk from Annual Risks

Our computations are built from a canonical model of earnings dynamics in which agents' earnings $y(t)$ at future time t may deviate from their expected path due to independent mean-zero log permanent ($\eta(t)$) or temporary ($\nu(t)$) earnings shocks:

$$\log y(t) = E[\log y(t)] + u(t), \text{ where} \tag{3}$$

$$u(t) = \pi(t) + \nu(t) \text{ and} \tag{4}$$

$$\pi(t) \equiv \int_0^t \eta(\tau)\, d\tau. \tag{5}$$

We allow the shocks' variances to vary over time, so call them $\sigma^2_\nu(t)$ and $\sigma^2_\eta(t)$. The estimation strategy does not require a distributional assumption, but we assume ν and η are normally distributed for the purpose of computing $\operatorname{Var} V$ (see footnote 1).

Several studies have estimated generalizations of this model (e.g., specifying the persistent shock as an autoregressive process), but results often indicate this simpler form fits the data well

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(MaCurdy 1982, Abowd and Card 1989, Meghir and Pistaferri 2004, Storesletten et al 2004, Hryshko 2012). It is especially convenient for our empirical strategy that π follows a random walk, as this allows us to estimate σ_ν^2 and σ_η^2 via closed-form statistics (see Section 3.1) rather than a system of equations.

Define $G(t) \equiv (1/t)\left[E \log y(t) - \log y(0)\right]$ as the mean expected earnings growth rate over the next t periods, and let $\delta(t) \equiv r - G(t)$, $h(\tau,\delta) \equiv \int_\tau^T e^{-\delta(t)\cdot t}\,dt$, and $\widetilde{V} \equiv V e^{\nu(0)}/y(0)$. Then

$$\widetilde{V} \approx \int_0^T e^{-\delta(t)\cdot t}\left[1+\nu(t)+\frac{1}{2}\left(\nu(t)\right)^2+\Xi\right]dt+\int_0^T h(t,\delta)\left[\eta(t)+\frac{1}{2}\left[\eta(t)\right]^2\right]dt, \tag{6}$$

where Ξ collects products of independent mean-zero random variables. Thus,[1]

$$E\widetilde{V} \approx \int_0^T e^{-\delta(t)\cdot t}\,dt + \frac{1}{2}\int_0^T e^{-\delta(t)\cdot t}\sigma_\nu^2(t)\,dt + \frac{1}{2}\int_0^T h(t,\delta)\sigma_\eta^2(t)\,dt, \text{ and} \tag{7}$$

$$\mathrm{Var}\,\widetilde{V} \approx \int_0^T e^{-2\delta(t)\cdot t}\left[\sigma_\nu^2(t)+\frac{1}{2}\sigma_\nu^4(t)\right]dt + \int_0^T \left[h(t,\delta)\right]^2\left[\sigma_\eta^2(t)+\frac{1}{2}\sigma_\eta^4(t)\right]dt. \tag{8}$$

For any assumed discount rate r, we can compute $E\widetilde{V}$, $\mathrm{Var}\,\widetilde{V}$, and $c^2 = \mathrm{Var}\,\widetilde{V}/\left(E\widetilde{V}\right)^2$ from three series we estimate for each agent: $\sigma_\nu^2(t)$, $\sigma_\eta^2(t)$, and $G(t)$. As needed, we calculate EV and $\mathrm{Var}\,V$ using predicted earnings (e.g., $EV \approx E\widetilde{V}\cdot Ey(0)$).

3 Estimating Heterogeneous Parameters

Our empirical model of earnings dynamics has been used in many previous studies:

$$y_{igt} = F_g\left(A_{it}\right) + Q_i\left(A_{it}\right) + u_{igt}, \tag{9}$$

[1]The derivation of (8) uses normality: $x \sim N\left(0,\sigma^2\right)$ implies $E\left(x^3\right)=0$ and $E\left(x^4\right)=3\sigma^4$. If we adapt our strategy for estimating σ_η^2 and σ_ν^2, the estimated third moments of η and ν are small relative to both the second moments and their own standard errors. Estimates of the fourth moments are too imprecise to draw strong conclusions, however.

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where y_{igt} is the log earnings in year t of agent i from group g, A_{it} is i's age, F_g is a group-specific age-earnings profile, and Q_i is a systematic deviation of i's earnings from F_g (see, e.g., Gordon 1984, Gottschalk and Moffitt 1994, Carroll and Samwick 1997, Haider 2001, Guvenen 2009). We interpret $F + Q$ as $E[\log y(t)]$ from equation (3) and residual u as $u(t) = \pi(t) + \nu(t)$ from (4).

Prior work finds ν is an MA(1) or MA(2) process (MaCurdy 1982, Abowd and Card 1989, Meghir and Pistaferri 2004), so we relax the independence assumption for ν to

$$E(\nu_{it}\nu_{it'}) = 0 \text{ for } |t - t'| \geq 3, \tag{10}$$

following Carroll and Samwick (1997). Like them, we estimate only σ_ν^2 itself, not the underlying MA parameters. While critical in other applications, their only impact on $E\widetilde{V}$ or $\operatorname{Var}\widetilde{V}$ would involve on-going effects of recent innovations, which typically comprise a tiny share of the total.[2]

3.1 Estimating Annual Earnings Risk

We compute heterogeneous estimates of $\sigma_\nu^2(t)$ and $\sigma_\eta^2(t)$ by adapting the strategies of Carroll and Samwick (1997) and especially Meghir and Pistaferri (2004). The idea is based on the expression implied by (4) and (5) for i's residual earnings growth $\Omega_i(t, t+k)$ between times t and $(t+k)$:

$$\Omega_i(t, t+k) \equiv u_{i(t+k)} - u_{it} = \nu_{i(t+k)} - \nu_{it} + \sum_{j=1}^{k} \eta_{i(t+j)}. \tag{11}$$

3.1.1 Permanent shocks

For each k and sufficiently large j and q, define a statistic

$$\gamma_{itkjq} \equiv \frac{1}{k}\Omega_i(t, t+k) \cdot \Omega_i(t-j, t+k+q). \tag{12}$$

[2] $E\widetilde{V}$'s temporary component already forms just 9 percent of mean $E\widetilde{V}$ (see Table 4), and with a known MA(1) process $\nu_t = \varepsilon_t + \varsigma\varepsilon_{t-1}$ and constant discounting (β), it would decrease by the small fraction $\varsigma^2\beta\sigma_\varepsilon^2(0)/\sum_{t=1}^{T}\beta^t\sigma_\nu^2(t)$.

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It is an unbiased (if noisy) estimator of the variance of annual permanent shocks:

$$E\left[\gamma_{tkjq}\right] = E\left[\frac{1}{k}\left(\nu_{i(t+k)} - \nu_{it} + \sum_{h=1}^{k}\eta_{i(t+h)}\right)\left(\nu_{i(t+k+q)} - \nu_{i(t-j)} + \sum_{h=1-j}^{k+q}\eta_{i(t+h)}\right)\right] = \frac{1}{k}\sum_{h=1}^{k}\sigma^2_{\eta i(t+h)} \tag{13}$$

Meghir and Pistaferri use (13) as the basis for a moment condition for $(k, j, q) = (1, 2, 2)$. Since our data become biennial, we instead use $k = 2$, so define $\gamma_{itjq} \equiv \gamma_{it2jq}$. We compute weighted averages γ_{it} of all γ_{itjq} with $j, q \geq 3$ to blunt the influence of large noise terms of forms $\nu_{it} \cdot \nu_{i\tau}$ or $\nu_{it} \cdot \eta_{i\tau}$; in our data, there can be as many as 367 γ_{itjq} for a given (i, t).[3] Since γ_{itjq} is noisier for larger j and q, the efficient weighted average is $\gamma_{it} \equiv \left(\sum_{j,q}\omega_{jq}\gamma_{itjq}\right) / \left(\sum_{j,q}\omega_{jq}\right)$, where $\omega_{jq} \equiv \left\{E_{jq}\left[\gamma_{itjq} - E_{it}\left(\gamma_{itjq}\right)\right]^2\right\}^{-1/2}$ and E_x is a sample mean given x.

To allow cross-sectional and intertemporal heterogeneity, we posit a linear relationship between worker i's characteristics X_{it} at time t and his risk at $t + \tau$, i.e., $E\left[\sigma^2_{\eta i(t+\tau)}|X_{it}\right] = X_{it}\psi_\tau$. We thus estimate $\sigma^2_{\eta i(t+\tau)}$ as fitted values from regressions[4]

$$\gamma_{i(t+\tau)} = X_{it}\psi_\tau + \epsilon_{it\tau}. \tag{14}$$

For example, we use $\widehat{\sigma}^2_{\eta i(1995)} \equiv X_{i(1990)}\widehat{\psi}_5$ as i's 1990 forecast of his 1995 annual risk. This can be viewed as an instrumental variables strategy to reduce measurement error (Carroll and Samwick 1997), i's rational expectation based on experiences of similar agents, or aggregation of similar cases to capture a wider set of potential outcomes (Saks and Shore 2005, Drewianka 2010).

Since ψ varies with the forecasting horizon τ, this approach imposes little structure on the progression of risk over agents' careers, as opposed to assuming, e.g., $\sigma^2_{\eta i(t+\tau)}$ changes at a constant rate. Some other studies have explicitly modelled forces like endogenous job search or occupational mobility that can cause $\sigma^2_{\eta i(t+\tau)}$ to differ from $\sigma^2_{\eta it}$ (Low et al 2010, Dillon 2018), which can

[3]Averaging is less effective against outlier noise terms of form $\eta_{it} \cdot \eta_{i\tau}$ because they could affect many γ's for a given (i, t), but this is a modest concern given that σ^2_ν is much larger than σ^2_η.

[4]The sampling variance of γ_{it} is roughly proportional to the number N_{it} of averaged γ_{itjq}'s, so we weight observations by $(N_{it})^{-1/2}$ to combat heteroskedasticity.

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be critical, e.g., for analyses in which it is important whether wage changes are caused by productivity shocks and or workers' responses to them. However, such issues are largely tangential to our goals here, and there is some danger in focusing on one potential mechanism to the exclusion of others, so we believe our more agnostic, data-driven approach is better suited for present purposes.

Regressions (14) also address the significant problem of missing data. There are many person-years for which we cannot compute $\gamma_{i(t+\tau)}$, e.g., because i did not participate or the survey was not conducted in that year. Even so, we can still compute $\widehat{\sigma}^2_{\eta i(t+\tau)}$ as long as we observe X_{it} and the data contain enough similar men to estimate ψ_τ. While we would obviously prefer to have complete data, using out-of-sample fitted values does not seem troubling given that the very premise is that risk can be measured from the collected outcomes of observably similarly workers.

3.1.2 Temporary shocks

A similar strategy is used to measure σ^2_ν. For each (i, t, j, q), define

$$\alpha_{itjq} \equiv -\Omega_i(t-j, t) \cdot \Omega_i(t, t+q). \tag{15}$$

Then for $j, q \geq 3$,

$$E\left[\alpha_{itjq}\right] \;=\; E\left[\left(\nu_{it} - \nu_{i(t-j)} + \sum_{h=j-1}^{0} \eta_{i(t-h)}\right)\left(\nu_{it} - \nu_{i(t+q)} - \sum_{h=1}^{q} \eta_{i(t+h)}\right)\right] = \sigma^2_{\nu i}(t). \tag{16}$$

As with the γ's, we construct α statistics for all available $j, q \geq 3$, create precision-weighted averages α_{it}, and estimate $\sigma^2_\nu(\tau)$ as fitted values from regressions like (14).

It should be noted that these estimates capture not only $\sigma^2_\nu(\tau)$, but also variation due to measurement error. However, our results indicate the $\widehat{\sigma}^2_\nu(\tau)$ series still comprises a small share of c^2, and the PSID Validation Study (Duncan et al 1985) finds few strong covariates of the variance of measurement error. Taken together, this suggests the bias in c^2 is small and approximately uniform.

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3.2 Estimating Expected Earnings Growth

The final series to estimate is i's expected annual earnings growth rate over the next τ years, $G_{it}(\tau)$. We start with the same residual earnings growth data $\Omega_i(t, t+\tau)$ we used to create γ and α above. At any time t, the predicted mean growth in i's annual earnings over the next τ years is $(1/\tau)\left[y_{i(t+\tau)} - y_{it} - \Omega_i(t, t+\tau)\right]$, so we use it as $G_{it}(\tau)$ when available. However, it is not available when agents' actual earnings are not observed in year $t+\tau$. When $G_{it}(\tau-1)$ and $G_{it}(\tau+1)$ can still be computed as above, we interpolate $G_{it}(\tau) = (1/2) * [G_{it}(\tau-1) + G_{it}(\tau+1)]$.

Otherwise we estimate $G_{it}(\tau)$ from that of similar observations; in other words, as out-of-sample fitted values from a regression like (14) in which the computable $G_{it}(\tau)$ are regressed against characteristics X. Since this may involve predicting earnings growth for a worker who will not actually work in the future year, the exercise estimates workers' expected potential earnings conditional on participation, even if the worker may eventually forego it (e.g., by retiring early).

4 Data

Our analysis uses data from the 1970-2015 waves of the Panel Study of Income Dynamics (PSID 2017), where possible using the coding of the Cross-National Equivalent File (CNEF) to ensure consistency across waves.[5] A given wave reports respondents' current characteristics and earnings in the previous year, and we use them to predict their earnings over the next year, which are reported in the wave gathered two years later. Despite the sample period, the longest possible panel has only 35 observations because the PSID became biennial in 1997.

We predict remaining lifetime earnings risk (through age 62) for men surveyed at ages 22-61. Since α and γ statistics require some data on subsequent earnings, the first stages of our estimation procedure also use somewhat older men (up to age 69) who remain in the labor force for at least

[5] See Burkhauser *et al.* (2000) for details on the CNEF. We did not use the CNEF's race codes, but instead created an algorithm that prefers self-reported information and uses responses from a wider array of questions. The main effect is that more respondents are classified as Hispanic.

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two years after the survey; this also improves long-term earnings forecasts for the youngest men by providing more observations on earnings growth over long periods. We exclude women because some variables are reported more regularly for men and because their lower rates of labor force attachment would raise the threat of mistaking intentional changes in labor supply for permanent earnings shocks. However, we retain men from the Survey of Economic Opportunity (SEO), an oversample of descendents of low-income families from 1966 and their spouses (Hill 1992), which more than quadruples the sample of non-whites.[6] We do not use sample weights, as our main goal is not to measure population averages, but to make predictions conditional on observables.

Our sample is more inclusive than those used in some prior work, which has often (usually for methodological necessity) restricted attention to prime-aged men who have never experienced a large change in earnings (e.g., $\left|\log(y_{i(t+1)}/y_{it})\right| > 1$) and have remained continuously in the sample as household heads. One consequence is that we find greater variances of raw- and residual earnings growth and larger σ_ν^2 than in those papers, though ours are very close to results from work on similarly-inclusive samples (Jensen and Shore 2015). We obtain similar results if we impose the same restrictions, but we opt not to do so because our method does not require them and we fear they tend to omit workers who have experienced the largest shocks and/or face the most risk.

Like most previous work, we estimate σ_ν^2 from data on log real annual earnings (in 2015 dollars),[7] which includes risk due to unemployment. However, changes in weeks worked that persist for many years likely reflect planned transitions (e.g. to new jobs with different schedules), not risk, so we instead estimate permanent risk σ_η^2 from data on log real weekly- and hourly wages.

More generally, we omit cases thought to reflect planned changes in labor supply, including

[6]Distributions of earnings, hours, hourly wages, ages, and education in the SEO are similar to those of same-race men in the main sample (Drewianka 2010), and any permanent differences between them would be removed when the data are differenced (Meghir and Pistaferri 2004). All our models include dummies for SEO status, but the estimates are usually small and statistically insignificant.

[7]Many of the largest ostensible earnings fluctuations in the PSID appear to reflect differences in earnings topcodes across waves (up to two orders of magnitude). We thus impose the same topcode for all waves, \$359,116.90 of real annual earnings — the smallest annual maximum. This change affects 511 observations (0.36 percent)

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all earnings data in years when respondents list their main activity as "student." We also do not use annual earnings for men who leave the labor force before the next survey, as it is unclear how the withdrawal accounts for changes in their weeks worked; we continue to use their weekly and hourly wage data. To exclude those with the weakest attachment, we drop annual earnings when it is less than $500, weekly wages based on fewer than 5 weeks worked or amounting to less than $100/week, and hourly wages based on fewer than 200 annual hours worked or less than $3/hour (about half the lowest real minimum wage over this era).

The explanatory variables fall into four broad categories. The first is demographic: age and racial groups, maximum levels of education, and birth cohorts. Another describes workers' careers: their current (or most recent) occupations and two-digit industries, years of job tenure, unemployment, non-participation, self-employment and union statuses, health-related limitations, and military service. A third factor is workers' recent earnings history, measured as workers' mean percentile in the annual earnings distributions of the previous five years.[8] Finally, to allow forecasts to vary with the business cycle (Storesletten et al 2004), we include two variables summarizing the macroeconomy at the time of the forecast (t): real GDP growth during year $(t-1)$ and Piger and Chauvet's (2017) estimated risk of recession in $(t+1)$. We also include indicators for missing data so that more observations can be retained, though we still drop those with many missing variables.

The Appendix explains how these variables enter our empirical specifications, and Section 5 documents some intermediate results. We are ultimately able to estimate c^2 for 134,552 person-year observations on 15,502 unique men. Table 1 reports summary statistics for that sample.

[TABLE 1 ABOUT HERE]

The PSID waves of 1999-2013 include data on households' wealth that we use to investigate θ, the share of men's lifetime budgets that are exposed to earnings risk. The wealth data cover many major assets (pensions, retirement accounts, owner-occupied real estate, stocks, bonds, farms and

[8] Earnings growth and risk are known to vary across the prior-earnings distribution (Guvenen, Ozkan, and Song 2014; Hardy and Ziliak 2014; Guvenen et al 2015; Guvenen et al 2017). While usually measured as quantiles of workers' total earnings over several years, our prior-earnings statistic accommodates biennial data and unbalanced panels.

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businesses owned) and liabilities (mortgages and other debts), but there are also some important shortcomings: the information is only available during a limited era that includes a major recession, and since wealth is reported at the household level, it seems appropriate to compute θ only for the likely-selected subsample who are household heads. We will thus devote less attention to these results, but they still warrant some discussion in view of θ's theoretical relevance.

5 Intermediate Results

Before turning to our main results about lifetime earnings risk, it may be helpful to summarize the intermediate estimates from which those main results are built, i.e., our estimates of workers' expected future earnings growth $G(\tau)$ and their expected future annual risks of permanent and temporary earnings shocks $\sigma^2_\eta(\tau)$ and $\sigma^2_\nu(\tau)$. The details of the specifications used to generate these estimates are explained in the Appendix.

Table 2 summarizes the estimates of earnings growth. The first column reports mean expected earnings growth over the coming year $G(1)$, while the remaining columns report mean growth forecasts over longer periods. We present stratified means because correlations between explanatory variables complicate interpretation of the regression coefficients; we hope it discourages unfounded causal interpretations as well. Standard analysis of variance rejects the hypothesis of homogeneous means within each of the listed categories at high levels of significance. The same is true in Tables 3 and 4 below, with only one exception (c^2 for self-employed and other men).

[TABLE 2 ABOUT HERE]

One notable pattern is that expected earnings growth rises after the first year: the mean of $G(1)$ is 0.1 percent, but the average worker's expected annual earnings growth is 10 times larger over the next 5-10 years, and it remains far above 0.1 percent even over very long periods. Some evidence suggests this reflects job laddering: the acceleration in occupations' expected earnings (the difference between the first two columns) is highly correlated with the shares of workers

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who moved to a new job (0.78) or an entirely new occupation (0.79) within the next six years. Regardless, this evidence cautions against models with steady expected earnings growth.

Earnings growth rates also vary more widely over longer periods. There are only a few factors for which $G(1)$ exceeds ± 1 percent, most of which describe workers entering or re-entering employment, whereas larger estimates are more common over longer horizons (especially for 5-10 years). The table shows a strong negative relationship between age and longer-term earnings growth, consistent with the familiar concave age-earnings profile. However, over all horizons we see higher expected long-term earnings growth for more educated workers, those who had not recently had a job, those at lower percentiles of the earnings distribution, and in years when a recession appears imminent (likely because earnings are depressed at the start of the period).

Table 3 summarizes estimates of σ_η^2 and σ_ν^2. The first two columns present estimated risks in the following year ($\tau = 0$), and the last two show means across all longer horizons ($\tau > 0$).

[TABLE 3 ABOUT HERE]

Our estimates align well with earlier results. Mean estimated σ_η^2 is just larger than 0.02, comparable to estimates by Carroll and Samwick (1997), Meghir and Pistaferri (2004), and Hryshko (2012), especially considering differences in the periods and dependent variables analyzed. While our mean estimate of σ_ν^2 (0.26) exceeds many reported earlier, the difference is fully due to our more inclusive sample (see page 11). Trends in both series are also echo earlier findings: mean σ_η^2 is stable (≈0.020) before the mid-1990s, but climbs over the next decade to about 0.025, while mean σ_ν^2 is countercyclical with a U-shaped longer-term trend that peaks in the early-1990s.

The most notable cross-sectional patterns appear to indicate that the nature of earnings risk differs across the earnings distribution. Temporary earnings risk correlates with several factors that predict lower wages or job security: Black or Hispanic ethnicity; lower education, job tenure, or recent earnings; jobs in food preparation or farming, fishing, or forestry; and being unemployed as of the survey. Since σ_ν^2 is much larger than σ_η^2, such factors are associated with larger year-to-year earnings fluctuations, in keeping with popular impressions about annual earnings risk. However,

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permanent earnings risk is instead associated with factors that predict *higher* income: White or Asian ethnicity; higher education or recent earnings; and employment in professional occupations and industries. While perhaps surprising, this is consistent with some prior work. Meghir and Pistaferri (2004) and Hryshko (2012) find similar relationships between risk and education, and recent evidence from Sweden (Friedrich et al 2019) indicates the wages of lower-earning workers are more sensitive to temporary firm-specific shocks, while firms' permanent productivity shocks mainly affect the earnings of higher-earning workers.

Several other patterns within the columns may also help to interpret the results below. Estimates of both σ^2_η and σ^2_ν follow a U-shape over the life-cycle and are larger for later birth cohorts. Both are high for non-participants re-entering the labor force, workers in volatile industries (restaurants, construction), and occupations that often use performance pay (sales, artists, personal services). Both are low for those shielded from business cycles by regulation or contracts (union members, mine workers, most non-profit and public subsectors), as well as production workers and those in most manufacturing subsectors.

We can also investigate annual earnings risk across forecasting horizons by comparing the first and last pairs of columns in Table 3. Two points seem most relevant: (a) the overall mean of $\sigma^2_{\eta(t+\tau)}$ across $\tau > 0$ exceeds the mean of $\sigma^2_{\eta t}$, and (b) many covariates of σ^2_η and σ^2_ν become weaker over longer forecasting horizons. In light of the positive relationship between σ^2_η and expected earnings noted above, we conjecture the former may reflect workers' systematic tendency to move to more lucrative jobs (with negative shocks reflecting failure to achieve prospective advancement), while the latter may arise because workers in riskier occupations are more likely to move to new occupations with different (though not systematically lower) levels of risk.

6 Main Results: Lifetime Earnings Risk

Once we have estimates of $\sigma^2_{\eta i(t+\tau)}$, $\sigma^2_{\nu i(t+\tau)}$, and $G_{it}(\tau)$, we can compute estimates of EV_{it}, $\mathrm{Var}\, V_{it}$, and c^2_{it} for any discount rate r. Lacking data on time preferences, we experimented with

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values ranging from 0.01 to 0.07, but fortunately estimates of c^2 are not very sensitive to r because its numerator and denominator change roughly proportionally. Each percentage-point increase in r reduces mean c^2 by less than 5 percent, and all are highly correlated (≥ 0.98) with those based on $r = 0.04$, so we simply report results using that value.

Table 4 reports means of the lifetime statistics for the full sample and stratified subsamples. The first column reports estimates of EV; its mean is \$996,500 and its cross-sectional standard deviation (not shown) is \$741,600. Some variation owes to year and age effects, but 79 percent of the variance is within age-year cells. The final lines show that 82 percent of mean EV comes from the expected log earnings path, with temporary and permanent risks responsible for 9 percent each (see the terms in equation (7)). The predictions are highly autocorrelated (e.g., $\mathrm{corr}(EV_t, EV_{t+6}) = 0.95$), consistent with permanent shocks being modest or infrequent.

[TABLE 4 ABOUT HERE]

The second column reports estimates of c^2. The overall mean is 0.106. This implies the average man faces ample uncertainty about his remaining lifetime earnings, with a 95 percent confidence interval of approximately $[(1/3)EV, (5/3)EV]$. This risk is not uniform across workers, however: the cross-sectional standard deviation of c^2 is about 30 percent of its mean.

Despite their inverse algebraic relationship, estimates of EV and c^2 are positively correlated across observations (0.25, both unconditionally and conditional on age and year), and even more so across occupations (0.55; see Figure 1). This has an important implication for empirical studies of choice: if EV and c^2 influence those choices in opposite directions, specifications that omit risk underestimate responses to riskless increases in expected lifetime earnings.

[FIGURE 1 ABOUT HERE]

The last lines of Table 4 show that permanent annual risk is responsible for the dominant share (87 percent) of lifetime risk. Even though estimates of σ^2_ν are roughly 10 times those of σ^2_η, the result is unsurprising given the difference in persistence. Consistent with that intuition, temporary

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risks account for just 4 percent of $\operatorname{Var} V$ for men in their 20s, but 58 percent for those over 55. Regardless, the finding provides reassurance that estimates of c^2 are not driven by misreporting in the earnings data (Duncan et al 1985), as that would cause overestimation of σ_ν^2, but not σ_η^2.

Since σ_η^2 rose over this era, this result suggests c^2 rose as well, and indeed the mean estimate of c^2 grows about 0.5 percent per year. However, as Figure 2 shows, the increase disproportionately affected more educated workers. While the time series for college graduates (16 years of schooling), high school graduates (12 years), and dropouts are all similar to the overall trend, the gaps are large and slightly expanding. Risk grew even faster for men with post-collegiate schooling, who had relatively low c^2 (similar to high school graduates') in the 1970s before converging toward college graduates' after the mid-1990s, while the reverse is true for those with some college.

[FIGURE 2 ABOUT HERE]

The last columns of Table 4 use estimates of θ computed from our EV estimates and the PSID's wealth data.[9] The main result is that wealth is modest relative to EV for most men, even though the men who report wealth data are apt to be wealthier than average. The mean θ is 0.88, its median is 0.96, and 73 percent of men under age 50 report net wealth less than $EV/10$. Thus, most men's total exposure to earnings risk (θc^2) is nearly as large as c^2 itself.

6.1 Covariates of Expected Future Earnings and Risk

Figure 3 depicts the evolution of EV, c^2, and θc^2 over the life-cycle.[10] It is not surprising that EV falls as workers age, but c^2 also declines over most of the life-cycle; $\operatorname{Var} V$ drops even faster than $(EV)^2$. The cross-sectional dispersion of c^2 also decreases steadily until about age 55, but after that it increases so much that mean c^2 rises even though the median c^2 continues to fall. This appears to

[9] Reported net wealth is negative for 1/5 of our sample. While $|W/EV|$ is small in most of those cases, we imposed $-EV/3$ as a lower bound on W to avoid negative θ (which would occur if $W < -EV$). This causes 98 men (0.3 percent) to have a top-coded value of $\theta = 1.5$.

[10] Figure 3 begins in 1999 because there is no earlier data on θ, but the lifecycle patterns of EV and $c^2$are similar over the entire sample period.

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reflect the heightened significance of temporary risks for the oldest workers: most outliers are aged 60-61 and have at least one trait that predicts high σ_ν^2 (e.g., self-employed; working in agriculture, construction, or legal services; jobs in sales or management; less than 2 years job tenure).

[FIGURE 3 ABOUT HERE]

As expected, future earnings comprise a decreasing share (θ) of the remaining lifetime budget as workers age. Both c^2 and θc^2 decline over most of the life-cycle, but θc^2 drops faster, and its late-career rise is later and much weaker than c^2's. Thus, even if some workers' remaining earnings grow riskier after their mid-50s, precautionary motives may not change much.

Given the life-cycle pattern in c^2, one might wonder whether we find higher c^2 is higher for more recent birth cohorts simply because workers from earlier cohorts appear more frequently in the data at older ages where c^2 is lower. Figure 4 resolves the issue by depicting the evolution of c^2 over the careers of nine cohorts, defined so as roughly to equalize their sample sizes. While all cohorts experienced similar life-cycle patterns, later cohorts have faced steadily greater risk. The highest line corresponds to the "Generation X" cohort, lending credibility to the heightened sense of vulnerability stereotypical to that group.

[FIGURE 4 ABOUT HERE]

Table 4 also explores the heterogeneity in lifetime earnings and risk along several dimensions. The covariates of EV are those one might imagine: larger for more educated men, younger workers, more recent birth cohorts, professionals, self-employed workers, Whites, Asians, and those with higher recent earnings. Given the algebraic relationship, one might expect covariates positively associated with EV to associate positively with θ too, but the table shows the relationship is more often negative, likely because men's past earnings became their current wealth.

In view of our goals, we are more interested in covariates of c^2 and θc^2. The covariates of c^2 broadly parallel those of σ_η^2, consistent with permanent shocks accounting for most of the variation in c^2. Factors associated with high levels of both c^2 and σ_η^2 include youth, education, nonparticipation, employment in restaurants or professional occupations and industries, and White,

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Asian, or Native American ethnicity, while both are below average for workers in manufacturing and the public- or non-profit sectors. A few differences are notable, though. While σ_η^2 bottoms out when workers are in their 40s, c^2 declines until nearly age 60. Neither union membership nor years of tenure is strongly related to σ_η^2, but both predict lower c^2. Across occupations, c^2 is larger than expected given σ_η^2 for scientific and military workers, but lower than expected for office workers.

Since θ is typically close to 1, θc^2 is highly correlated with c^2, and they tend to have the same covariates. However, some factors vary less reliably with θc^2 because their relationships to c^2 and θ are in opposite directions—e.g., c^2 has a U-shaped relationship with men's recent earnings percentiles, but θc^2 declines steadily. Likewise, despite facing high risk of temporary shocks and average risk of permanent shocks, the lifetime earnings risk of self-employed men is a bit below average and (reflecting their relatively high wealth) their mean θc^2 is among the lowest in Table 4.

6.2 Lifetime Earnings Risk versus Short-Term Measures of Risk

To illustrate the distinction between annual and lifetime earnings risk, Table 5 reports correlations between c^2 and θc^2 and four alternate measures of annual earnings risk. Three of the four are only weakly correlated (≤ 0.3) with c^2, and even less so with θc^2: predicted squared residual earnings $E[u_{it}^2|X_{it}]$, predicted squared residual biennial growth $E\left[[\Omega_i(t,t+2)]^2\,|X_{it}\right]$, and estimated σ_ν^2.

[TABLE 5 ABOUT HERE]

Moreover, each of those measures is least correlated with lifetime earnings risk for young to middle-aged workers. This is unsurprising given that younger workers are more apt to change jobs and that short-term earnings comprise a smaller share of their EV, and it parallels earlier findings on the relationship between workers' annual earnings and permanent incomes (Bjorklund 1993, Haider and Solon 2006). Even so, considering that young people make many decisions with long-term ramifications, the low correlations at young ages suggest that estimates based on annual measures of risk may greatly understate behavioral responses to lifetime risk.

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Differences are smaller for the risk of permanent annual shocks (σ_η^2). While its correlation with θc^2 is still moderate (0.26), it is more strongly correlated with c^2 (0.52), especially among prime-aged men (≥ 0.7). Since some empirical studies have taken pains to isolate or emphasize persistent annual risks (e.g., Carroll and Samwick 1997, Saks and Shore 2005, Santos and Weiss 2016, Sommer 2016), this result may seem reassuring. Nevertheless, the next exercise will show that c^2 has greater predictive power than σ_η^2 for several important decisions.

6.3 How Sensitive Are Choices to Measures of Risk?

The four panels of Table 6 present estimated mean marginal elasticities of measures of income and risk on outcomes for which lifetime risk is plausibly relevant: becoming a household head for the first time, marrying for the first time, buying a house, and the amount spent on a newly purchased house. The main goal is to provide some validation of both our estimates and our emphasis on lifetime measures. While most of the key elasticities are fairly large, we resist the temptation to draw strong quantitative conclusions, as all these issues surely warrant more extensive analysis. Instead, the idea here is that agents' decisions will only vary closely with measures of earnings and/or risk that capture relevant information. For example, the estimated elasticities with respect to c^2 would be small either if c^2 were a poor measure of risk or if agents were indifferent to it.

First, a few details are in order. The results in panels A and B come from Cox proportional hazards models, those in panel C are from a probit with random effects, and the last panel reports regressions on log prices.[11] The focal explanatory variables may be lifetime measures of expected earnings and risk (EV and c^2), annual earnings and variances of permanent and temporary shocks (y_t, σ_η^2, and σ_ν^2), or all of them; we exclude θ because sample sizes would drop sharply and become less representative. Similar results emerge from other variations not shown, including using probits (with or without random effects) instead of Cox models, using expected squared residuals ($E[u_t^2|X]$) in lieu of σ_η^2 and σ_ν^2, and estimating panels C and D jointly to address selection.[12] All

[11]The transitions to first headship and first marriage are largely separate events. They are concurrent for only 3 percent of first headships and 6 percent of first marriages in the data.

[12]The last of these is essentially Heckman's (1979) model with random effects in the selection equation; we used a

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specifications include many factors used to construct EV and c^2, such as demographics, education, employment status, years, and Census divisions, but not occupations, industries, or job conditions.

One caveat is that the standard errors in Table 6 have not been adjusted for the generated-regressors problem. The computational burden of the usual block-bootstrap correction is unusually high here because both the process of computing the lifetime statistics (EV, c^2) and the maximum likelihood estimation procedures for panels A-C are quite slow. However, results for the most readily-computed cases (panel D) indicate the corrections are modest and would not substantially alter the interpretation. For the model with σ_η^2, and σ_ν^2, bootstrapping raises their standard errors by 18 percent, and in the first two models there is virtually no effect on the standard error of the c^2 coefficient, while EV's rises from 0.02 to 0.03-0.04.[13]

[TABLE 6 ABOUT HERE]

The estimates in Table 6 support three main conclusions. First, all these choices are sensitive to our measure of lifetime earnings risk. The elasticities of both headship and marriage choices with respect to c^2 are much larger than those of the other listed variables. While c^2 does not vary as widely across the population as EV, its elasticity is so much larger that it still accounts for more of the variation in both choices. The house purchase decision is also most sensitive to c^2, with an elasticity greater than 1 in magnitude, though EV's elasticity is nearly as large. House prices are less sensitive to c^2, but the elasticity is still -0.27 and statistically significant.

Second, all these choices are more sensitive to the lifetime measures (EV and c^2) than to their annual analogues (y_t, σ_η^2, and σ_ν^2). If the latter were good proxies for the former, the elasticities in columns 3 and 4 should be at least similar to those in columns 1 and 2, but they are always smaller (often much smaller, though a few are still moderate), and their goodness-of-fit is worse too. The point is reinforced when we include all five measures (column 5): the elasticities for EV and c^2

dummy for men's prior headship status as an excluded variable. While this is a significant predictor of home purchases, the estimates do not reject the hypothesis of no selection.

[13] To avoid the burden of computing the lifetime statistics multiple times, in those specifications we instead adjusted the standard errors via the technique of Murphy and Topel (1985).

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remain much larger and at times grow. Since we control for age, this is not simply due to differing career horizons, but rather suggests agents anticipate facing different annual risks in the future.

Finally, the estimates shed some light on potential biases in specifications that omit risk; earlier we argued this may cause effects of EV to be understated. While some differences are reassuringly small, the estimated elasticities with respect to EV are invariably larger when c^2 is included, and they rise by 26 and 37 percent for the headship and marriage hazards, respectively. Estimates for the control variables (not shown) tell a similar story: in most cases adding c^2 makes little difference, but, e.g., several initially-significant age group coefficients drop 55-105 percent in the home purchase probit and by 20-30 percent in the house price regression. Thus, while omitting risk does not necessarily cause major biases, a few results illustrate more troubling possibilities.

7 Discussion

This paper has estimated the uncertainty in the present value of workers' potential earnings over their remaining careers and described how that risk varies over time, within careers, and across the population. Such risk seems most likely to affect choices that would require substantial commitment by agents whose earnings streams will not be fully realized for many years. Some previous work has instead studied the role of risk in such contexts using workers' annual risks of permanent earnings shocks, so our most critical finding may be that it is often a flawed proxy for lifetime earnings risk. While we find a reasonably strong correlation between the two for mid-career workers, the relationship is weaker for the younger individuals who often face major life decisions, and we identified several choices that vary more closely with lifetime risk than with annual risk.

Our empirical strategy includes several mechanisms that allow lifetime risk to diverge from annual risk, but we suspect the most important is the evolution of annual risk over workers' careers. Other factors like differences in remaining career lengths and expected future earnings growth also create separation, but such gaps would likely narrow considerably when conditioned on workers' ages and levels of education, as is common in studies of behavior. A similar idea has recently been

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advanced by Chang et al (2018), who propose decreases in annual earnings risk over the life-cycle as a reason why investment portfolios often take on more (not less) risk as individuals age.

Future work might refine our estimates by investigating potential means of managing earnings risk. For example, with appropriate data, one might incorporate other sources of income and costs like taxes, transfers, and earnings of other household members. Since it is widely understood that the option to adjust one's labor supply provides an important form of insurance against earnings shocks, a model that endogenized retirement may provide a valuable extension as well.

Appendix: Implementation

The empirical strategy outlined earlier builds from measures of workers' residual earnings growth $\Omega(t, t+j)$ between each pair of periods. We construct those residuals in two steps. We first collect residuals ξ_{it} from regression (9). The specification includes separate quartic age-earnings profiles F_g for 32 groups defined by combinations of men's broadly-defined race (white or non-white), birth cohort (before 1944, 1944-1952, 1953-1960, after 1960), and maximum level of education (0-11, 12, 13-15, and 16+ years), plus another quartic that allows earnings paths of men with 17+ years of schooling to differ from those of other college graduates in their group, as well as age and year dummies and linear trends for each level of education and census division.

Men's predictable deviations Q_i from those profiles are modeled as fixed effects, which are removed when the data are differenced. There has been some controversy about whether models should also allow for individual trends (MaCurdy 1982; Guvenen 2007, 2009; Hryshko 2012), but Drewianka and Oberg (2019) present several reasons to favor a fixed effects specification when estimating the risk of permanent shocks. Perhaps most strikingly, they explain why models with individual trends bias estimates of σ_η^2 downward, in practice causing most estimated $\sigma_{\eta i}^2$ to become negative. Our fixed effects specification avoids those pitfalls, yet still allows considerable heterogeneity in expected growth via the group-specific age-earnings profiles.

While that first step removes systematic variation in workers' long-run expected earnings and

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aggregate shocks, their forecasts of their entire future earnings profile should also be updated each period to reflect new information. We thus add a second step that removes that variation by regressing workers' residual earnings growth $\widetilde{\Omega}_i(t, t+j) \equiv \xi_{i(t+j)} - \xi_{it}$ over each j-year period ($j = 1, ..., 39$) against explanatory variables reported one year before the period began (e.g., jobs reported in 1990 are used to predict earnings growth between 1991 and each future date). Explanatory variables in these regressions include all demographic dummies, a spline in age, a spline in time for each level of education, and decade-specific dummies for all job characteristics and quadratics in men's recent earnings percentiles. We interpret the residuals as the Ω from equation (11). Note that this step ensures Ω is orthogonal to the variables that will later be used to forecast risk, reducing the risk that predictable earnings growth is misinterpreted as risk.

Nonetheless, in practice this second step plays only a minor quantitative role. Despite the extensive specification, about 3/4 of the explained variation in raw earnings growth rates $\log\left(y_{(t+j)}/y_t\right)$ occurs in the first-step, so most of what we classify as expected growth simply reflects the group age-earnings profiles and year dummies. (Indeed, the two steps together account for only a tiny share of the variation in $\log\left(y_{(t+j)}/y_t\right)$ for short periods j, and only a moderate share over longer periods, e.g., 21 percent for $j = 20$.) Consequently, eliminating the second step causes only small changes in our main estimates: mean EV, c^2, σ_η^2, and σ_ν^2 all rise by 1-9 percent, and all are highly correlated (> 0.94) with our preferred estimates reported below.

This robustness is especially reassuring in view of some earlier work in which results have been sensitive to whether the earnings process was estimated in levels or differences (Heathcote et al 2010). We conjecture that two features of our methodology help us avoid that fate. First, unlike those studies, we do not use any moment conditions involving squared residuals (contrast equation (12) with $\Omega_i(t, t+1)^2$), so here specification error would have to be systematically correlated across periods to introduce bias. Second, all our α and γ statistics use residual growth $\Omega_i(t, t+j)$ over at least one period with $j \geq 3$ (see equation (10)); Carroll (1992) shows that when temporary earnings follow an MA(q) process, estimates become less sensitive to the levels/differences specification when residual growth is measured over periods longer than q.

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Expected earnings growth

As noted in Section 3, where possible we use the expected earnings regressions to predict $G_{it}(\tau)$, i's expected mean annual earnings growth between t and $t+\tau$. Where that is not possible (e.g., when $t+\tau > 2015$), we estimate it via regressions akin to (14). The specification includes the major factors used to predict the age-earnings profiles: dummies for demographics, job characteristics, the current year (t) and i's age in year ($t+\tau$); quadratics in his current age for four forecasting horizons τ (the next year and 1-2, 3-4, and 5+ years into the future) and in the earnings history variable; and a spline in job tenure. Since education effects are known to vary over time and the life-cycle, we interact each broad level of education with a time trend and dummies for five future-age groups (22-25, 26-35, 36-45, 46-55, and 56-62). To limit the Great Recession's influence, we force future-year trends to have a constant effect after 2005 in all regressions of type (14).

Estimating annual risks

Since our estimation strategy uses combinations of residual earnings growth Ω over differing periods for each i (see Section 3), we obtain a large number of risk statistics: about 6 million γ_{itjq}'s and 4 million α_{itjq}'s for each measure of earnings. As described above, weighted averages of those statistics are the dependent variables when we forecast agents' future risks $\sigma^2_{\eta i(t+\tau)}$ and $\sigma^2_{\nu i(t+\tau)}$.

The specifications for those forecasts parallel those used for expected earnings growth, with two exceptions. First, effects of job characteristics are now allowed to vary across four forecasting horizons τ. Among other things, this captures variation in rates at which workers move to new jobs that would alter their annual earnings risk in future years—e.g., a restaurant worker in 1997 may anticipate a high probability of remaining in that industry in 1998, but a far greater chance of being in a new industry with different levels and types of risk by 2005. The macroeconomic variables are also interacted with the time-horizon dummies to allow volatility to vary over the business cycle.[14]

[14] A more flexible specification is more practical here than in the earnings growth regressions due to the reduced noise in the dependent variables. While there is only one way to compute actual earnings growth $\left[y_{i(t+\tau)} - y_{it}\right]/\tau$ for a given (i,t), γ_{it} is an average of many γ_{itjq} statistics.

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Second, the regressions now include a quadratic in the mean value of $(j + q)$ across the (e.g.) γ_{itjq} statistics used to construct γ_{it}. This addresses biases due to non-random attrition, such as if large negative shocks caused withdrawal from the labor force or large positive shocks allowed earlier retirements. Conditional on other controls, γ and α are indeed decreasing in mean ($j + q$), so we compute fitted values using the smallest observed ($j + q$) to offset the apparent bias.

We compute separate estimates of $\sigma^2_{\eta i(t+\tau)}$ and $\sigma^2_{\nu i(t+\tau)}$ based on each measure of earnings (annual, weekly, and hourly). Those based on weekly and hourly earnings are highly correlated (0.82 for σ^2_η, 0.91 for σ^2_ν), but less so with those based on annual earnings (0.51 to 0.66), which are also about 50 percent larger. For $\sigma^2_{\nu i(t+\tau)}$, we prefer the estimate based on annual earnings because it includes shocks related to unemployment, but we replace it with a standard-error weighted average of all three estimates when both others are larger (about 10 percent of (i, t, τ)). Our preferred estimate of $\sigma^2_{\eta i(t+\tau)}$ is a standard error-weighted average of the weekly- and hourly-based estimates, with the small number of negative fitted values reset to zero (0.07 percent of cases with weekly earnings, 0.3 percent with hourly earnings; nearly all were small relative to their standard errors).

The distributions of γ and α statistics have long tails, so we considered winsorizing to curb the influence of outliers, but it mainly just reduced estimates of σ^2_ν. Winsorized estimates of σ^2_η, σ^2_ν, EV, $\text{Var}\,V$, and c^2 are all highly correlated (> 0.97) with the (unwinsorized) estimates we report.

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Table 1: Summary Statistics

Dependent variables	**Mean**	**SD**		**Number**	**Share**
log earnings/year	10.67	0.85	Birth Cohorts		
log earnings/week	6.91	0.67	Before 1944	30,991	23.0
log earnings/hour	3.10	0.63	1944-1952	34,697	25.8
Independent variables	**Mean**	**SD**	1953-1960	33,984	25.3
Age	37.0	10.4	1961 and later	34,880	25.9
Years of schooling	13.3	2.6	Employment characteristics		
Years of tenure on job	3.7	6.3	Unemployed (at survey)	5,895	4.4
	Number	**Share**	Out of labor force (at survey)	2,766	2.1
Race			Self-employed	15,113	11.2
White	82,734	61.5	Tenure: less than 2 years	79,180	58.9
Black	38,057	28.3	Paid on hourly basis	59,199	44.0
Hispanic	9,180	6.8	Union member/covered	26,491	19.7
Native American	2,654	2.0	Has work limitations	10,636	7.9
Asian/Pacific Islander	1,107	0.8	Military veteran	52,549	39.1
Other	820	0.6	Industries		
Education			Retail Trade	11,880	8.8
Less than 12 years	18,879	14.0	Business/Professional Services	10,157	7.6
12 years	46,595	34.6	Construction Related	9,822	7.3
13-15 years	32,747	24.3	Public Administration	9,103	6.8
16 years	18,805	14.0	Mechanical Engineering	7,562	5.6
More than 16 years	17,526	13.0	Other Transportation	5,917	4.4
Occupations			Education/Sports	5,846	4.3
Construction/Extraction/Repair/Etc.	21,352	15.9	Wholesale Trade	5,772	4.3
Management	16,127	12.0	Wood/Paper/Print	5,529	4.1
Production	14,683	10.9	Agriculture & Forestry	4,310	3.2
Transportation & Material Moving	13,690	10.2	Health Services	4,095	3.0
Office & Administrative Support	10,049	7.5	Clothing/Textiles	3,872	2.9
Farming, Fishing, & Forestry	7,363	5.5	Construction	3,757	2.8
Sales & Related	5,439	4.0	Electrical Engineering	3,416	2.5
Architecture & Engineering	5,087	3.8	Iron/Steel	3,348	2.5
Building/ Grounds Cleaning & Maint.	3,251	2.4	Energy/Water	3,305	2.5
Protective Service	3,213	2.4	Postal System	3,164	2.4
Education, Training, & Library	2,865	2.1	Food Industry	2,566	1.9
Computer & Mathematical	2,677	2.0	Legal Services	2,139	1.6
Food Preparation & Serving Related	2,531	1.9	Financial Institutions	1,923	1.4
Military Specific	2,429	1.8	Chemicals	1,810	1.4
Life, Physical, & Social Science	2,170	1.6	Restaurants	1,734	1.3
Healthcare Support	1,542	1.2	Insurance	1,678	1.3
Business & Financial Operations	1,450	1.1	Personal Services/Recreation	1,667	1.2
Arts/Design/Entert./Sports/Media	1,337	1.0	Volunteer/Church	1,537	1.1
Healthcare Practitioners & Tech.	955	0.7	Synthetics	1,137	0.9
Legal	927	0.7	Mining	1,096	0.8
Personal Care & Service	685	0.5	Earth/Clay/Stone	963	0.7
Community/Social Services	488	0.4	Train System	729	0.5
Other/Unknown	14,242	10.6	Other/Unknown Industry	14,718	10.9
Total annual observations	134,552		Unique individuals	15,502	

Notes: The table reports summary statistics for observations for which our measure of lifetime earnings risk can be calculated, which is about 98 percent of the observations on men aged 22-61 in the 1970-2013 waves of the PSID who also met the sample inclusion criteria (specified in the text) in the waves gathered two years later (1972-2015). Years of schooling are the maximum ever reported by the individual. Occupations and industries are for the men's current main job as of the survey, or (if any) their most recent reported main job within the preceding four years. The sample size is for annual earnings; there are 3% fewer observations on weekly or hourly wages.

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Table 2: Expected Average Annual Real Earnings Growth Rate, by Covariates

Avg over next x yrs:	1	5-10	15-20	25-30
Overall	0.1	1.0	0.7	0.7
Age groups				
22-25	0.2	4.0	2.6	1.8
26-35	0.0	1.8	1.0	0.3
36-45	-0.1	0.0	-0.7	-0.7
46-55	0.3	-1.6	-1.9	
Over 55	0.1	-2.6		
Education				
Less than 12 years	-0.5	-0.1	0.0	0.5
12 years	-0.4	0.7	0.6	0.6
13-15 years	0.0	1.2	0.7	0.6
16 years	0.9	1.9	1.2	1.1
More than 16 years	1.3	1.9	1.3	1.1
Employment characteristics				
Unemployed	1.8	3.2	2.7	2.6
Out of labor force	1.1	3.4	2.7	2.2
Self-employed	0.3	0.5	0.3	0.5
Paid on hourly basis	-0.1	1.2	0.9	0.9
Union member/covered	-0.6	0.0	-0.2	-0.1
Has work limitations	0.1	0.4	0.4	0.5
Military Veteran	-0.1	0.3	0.2	0.4
Industries				
Other/Unknown Industry	1.0	3.6	2.7	2.2
Agriculture & Forestry	0.7	1.4	1.2	1.3
Financial Institutions	1.3	2.2	1.6	1.3
Insurance	1.1	1.6	1.2	1.2
Personal Services/Recr.	0.4	1.2	0.9	0.9
Volunteer/Church	0.7	1.0	0.7	0.7
Education/Sports	0.8	1.2	0.8	0.7
Health Services	0.6	1.1	0.7	0.6
Construction	-0.2	0.9	0.5	0.6
Public Administration	0.2	1.0	0.6	0.5
Wholesale Trade	0.0	0.7	0.5	0.5
Legal Services	0.4	0.7	0.4	0.4
Mechanical Engineering	-0.2	0.5	0.3	0.4
Retail Trade	-0.2	0.8	0.5	0.4
Chemicals	0.1	0.8	0.4	0.4
Wood/Paper/Print	-0.4	0.5	0.3	0.4
Food Industry	-0.2	0.4	0.3	0.3
Electrical Engineering	-0.1	0.5	0.2	0.3
Energy/Water	-0.3	0.4	0.2	0.3
Construction Related	-0.3	0.5	0.2	0.3
Other Transportation	-0.2	0.3	0.1	0.3
Business/Prof Services	0.0	0.8	0.3	0.2
Restaurants	-0.2	1.1	0.4	0.1
Earth/Clay/Stone	-0.8	0.0	-0.1	0.1
Synthetics	-0.6	0.2	-0.1	0.0
Postal System	-0.3	0.3	0.0	0.0
Iron/Steel	-0.8	0.1	-0.1	-0.1
Clothing/Textiles	-0.5	0.1	-0.2	-0.2
Train System	-0.8	-0.2	-0.3	-0.2
Mining	-1.3	-0.3	-0.6	-0.6

	1	5-10	15-20	25-30
Birth cohorts				
Before 1946	-0.1	-0.9	-0.9	-0.4
1946-1952	0.0	0.9	0.4	0.4
1953-1959	0.1	1.4	1.1	1.0
1960 and later	0.3	2.2	1.2	0.9
Race				
Asian/Pacific Islander	0.9	1.0	0.7	1.0
Hispanic	0.1	1.2	0.8	0.8
Black	-0.1	1.0	0.7	0.7
White	0.2	1.1	0.7	0.7
Other	0.1	0.4	0.2	0.5
Native American	-0.2	0.5	0.2	0.4
Job tenure				
Less than 2 years	0.4	1.7	1.2	1.1
2-5 years	-0.5	0.5	0.1	-0.1
5 plus years	-0.3	-0.5	-0.6	-0.4
Unknown	0.4	2.0	1.6	1.6
Occupations				
Architecture & Engineering	0.7	1.3	0.9	0.8
Arts/Design/Entert./Sports/Media	0.4	1.2	0.7	0.5
Building/ Grounds Cleaning & Main	-0.3	0.4	0.3	0.3
Business & Financial Operations	0.7	1.3	0.8	0.6
Community/Social Services	1.3	1.6	1.3	1.2
Computer & Mathematical	0.2	0.9	0.3	0.1
Construction/Extraction/Repair/Etc.	-0.5	0.5	0.2	0.2
Education, Training, & Library	0.9	1.4	0.7	0.5
Farming, Fishing, & Forestry	0.1	0.7	0.6	0.7
Food Preparation & Serving Related	0.2	1.6	1.1	0.9
Healthcare Practitioners & Tech.	1.6	1.6	1.0	1.1
Healthcare Support	0.4	1.1	0.8	0.6
Legal	1.9	1.8	1.2	1.2
Life, Physical, & Social Science	0.7	1.2	0.7	0.6
Management	0.3	0.4	0.2	0.4
Military Specific	0.5	2.3	1.3	1.0
Office & Administrative Support	0.1	0.8	0.3	0.2
Other/Unknown	1.1	3.8	2.9	2.4
Personal Care & Service	0.4	1.4	1.0	0.8
Production	-0.6	0.3	0.1	0.1
Protective Service	-0.1	0.7	0.3	0.2
Sales & Related	0.5	1.3	0.9	0.8
Transportation & Material Moving	-0.6	0.2	0.1	0.2
Mean earnings percentile, prev. 5 years				
0 to 20	0.7	1.8	1.6	1.7
20 to 40	0.2	1.1	0.9	0.9
40 to 60	-0.1	0.8	0.5	0.4
60 to 80	-0.3	0.4	0.1	0.0
80 to 100	-0.2	0.2	-0.2	-0.3
No reported earnings in prev. 5 yrs.	1.2	3.5	2.7	2.4
Business cycle				
Real GDP/capita growth > 3 pct	-0.2	0.8	0.7	0.8
Real GDP/capita growth < 0 pct	-0.2	1.3	0.6	0.6
Prob of recession < 10 pct	0.1	0.9	0.7	0.7
Prob of recession > 50 pct	0.8	2.4	1.4	1.4

Note: The figures reported are the expected mean annual real earnings growth between years t+1 and t+1+x, as predicted based on characteristics available in year t. Stratified means are for all observations with the listed characteristic. Racial groups, industries, and occupations are listed in decreasing order of expected long-term earnings growth.

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Table 3: Means of Permanent and Temporary Earnings Volatility (x100), by Covariates

	Next year		All future years	
	Perm	Temp	Perm	Temp
Overall	2.1	26.1	2.3	24.0
(Standard deviation)	0.8	18.7	0.9	10.9
(Avg. SE of prediction)	0.6	7.2	0.5	7.2
Age groups				
22-25	2.2	34.7	2.3	25.1
26-35	2.2	27.1	2.3	23.9
36-45	1.9	21.6	2.4	23.1
46-55	2.1	23.7	2.5	24.0
Over 55	2.6	25.7	2.9	26.1
Education				
Less than 12 years	1.9	27.2	1.7	23.3
12 years	2.0	28.5	2.3	24.6
13-15 years	2.1	24.9	2.3	22.2
16 years	2.5	24.5	2.7	27.2
More than 16 years	2.3	22.3	2.8	23.4
Employment characteristics				
Unemployed	1.9	64.8	2.4	37.3
Out of labor force	3.0	76.2	2.5	30.9
Self-employed	2.2	39.4	2.6	35.8
Paid on hourly basis	2.0	27.7	2.2	24.2
Union member/covered	2.1	18.3	2.2	19.6
Has work limitations	2.1	30.1	2.4	27.3
Military Veteran	2.0	25.5	2.3	24.2
Industries				
Chemicals	1.7	13.3	2.2	13.9
Electrical Engineering	1.7	13.8	2.2	23.9
Volunteer/Church	1.6	14.5	2.4	21.6
Insurance	2.5	14.6	2.4	15.8
Public Administration	1.9	16.6	2.5	18.7
Education/Sports	1.8	16.6	2.3	19.5
Postal System	1.7	17.2	1.9	19.1
Clothing/Textiles	1.8	17.3	2.4	19.4
Food Industry	2.3	17.6	2.4	18.6
Energy/Water	2.2	18.7	2.2	20.5
Financial Institutions	2.7	18.7	2.5	21.2
Earth/Clay/Stone	1.9	18.7	2.0	28.8
Synthetics	1.7	19.3	2.1	21.6
Wood/Paper/Print	2.1	19.6	2.5	21.2
Health Services	2.5	19.8	2.6	22.1
Iron/Steel	2.0	20.1	2.2	22.3
Wholesale Trade	2.0	21.0	2.2	21.6
Mechanical Engineering	1.8	21.2	2.2	20.5
Other Transportation	2.2	21.7	2.2	20.7
Mining	2.0	22.2	2.2	23.8
Construction Related	2.0	23.7	2.1	23.4
Retail Trade	2.1	24.2	2.5	22.7
Legal Services	2.6	26.6	2.7	27.8
Bus/Prof Services	2.5	28.6	2.6	29.8
Restaurants	2.7	28.7	2.4	24.5
Train System	1.8	29.2	2.6	23.4
Construction	2.3	32.2	2.3	29.1
Personal Services/Recr.	1.9	34.2	2.4	24.7
Agriculture & Forestry	2.1	45.7	2.4	43.9
Other/Unknown Industry	2.5	56.9	2.4	29.7

	Next year		All future years	
	Perm	Temp	Perm	Temp
Birth cohorts				
Before 1946	1.9	23.8	2.2	23.0
1946-1952	2.1	24.5	2.3	22.8
1953-1959	2.0	26.8	2.2	24.0
1960 and later	2.5	29.0	2.5	25.5
Race				
Native American	2.2	23.0	2.5	21.2
Asian/Pacific Islander	2.4	23.2	2.5	23.0
White	2.2	24.2	2.4	23.4
Black	2.0	29.5	2.2	25.0
Hispanic	2.0	29.5	2.1	25.5
Other	2.0	31.3	2.2	28.9
Job tenure				
Less than 2 years	2.1	31.0	2.4	25.5
2-5 years	2.3	18.2	2.3	21.6
5 plus years	2.1	18.3	2.3	20.9
Unknown	1.9	34.5	2.5	26.0
Occupations				
Business & Financial Operations	2.3	12.5	2.4	20.5
Architecture & Engineering	2.4	14.1	2.5	17.3
Community/Social Services	1.6	14.9	2.6	15.4
Education, Training, & Library	1.7	15.5	2.5	18.6
Life, Physical, & Social Science	2.2	15.8	3.1	21.3
Legal	2.4	16.1	2.7	17.2
Computer & Mathematical	2.2	16.7	2.5	30.7
Healthcare Practitioners & Tech.	3.1	17.4	2.9	20.1
Military Specific	2.2	18.8	2.8	20.3
Healthcare Support	2.1	19.2	2.2	16.7
Protective Service	2.0	20.0	2.3	21.5
Management	2.2	20.0	2.6	21.9
Production	1.8	20.5	2.1	19.2
Office & Administrative Support	2.5	20.7	2.4	25.3
Building/ Grounds Cleaning & Maint.	2.0	22.1	2.3	25.2
Arts/Design/Entert./Sports/Media	2.5	23.6	2.9	23.2
Sales & Related	2.3	23.9	2.5	25.1
Transportation & Material Moving	1.7	24.5	2.1	23.4
Construction/Extraction/Repair/Etc.	2.0	25.2	2.1	23.4
Personal Care & Service	2.5	28.6	2.4	26.2
Food Preparation & Serving Related	2.0	29.4	2.3	24.9
Farming, Fishing, & Forestry	2.0	32.8	2.3	33.8
Other/Unknown	2.5	59.2	2.4	30.1
Mean earnings percentile, prev. 5 years				
0 to 20	2.1	38.5	2.4	31.3
20 to 40	2.0	27.3	2.3	25.9
40 to 60	2.0	22.1	2.3	22.8
60 to 80	2.1	18.5	2.3	20.7
80 to 100	2.3	17.1	2.5	20.3
No reported earnings in prev. 5 yrs.	2.6	54.1	2.4	26.2
Business cycle				
Real GDP/capita growth > 3 pct	1.9	26.1	2.2	23.2
Real GDP/capita growth < 0 pct	2.3	25.7	2.4	24.1
Prob of recession < 10 pct	2.1	25.5	2.4	24.0
Prob of recession > 50 pct	1.9	30.9	2.2	23.5
Number of observations (x1,000)	135	135	3,362	3,362

Note: Estimated volatility of temporary shocks is based on annual earnings, and that of permanent shocks is a weighted average of estimates based on weekly and hourly earnings. Employment characteristics are as of the survey date. Racial groups, industries, and occupations are listed in increasing order of estimated risk of temporary shocks over the next year.

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Table 4: Means of Present Value of Future Earnings (EV) and Its Coefficient of Variation (c^2), by Covariates

	EV / 1,000	$100\cdot c^2$	$100\cdot\theta$	$100\cdot c^2\cdot\theta$
Overall	996	10.6	87.7	9.7
Age groups				
22-25	1,195	13.6	99.9	14.7
26-35	1,213	11.6	97.7	12.5
36-45	1,008	9.1	91.4	9.1
46-55	629	7.8	79.8	6.9
Over 55	222	11.4	56.5	6.3
Education				
Less than 12 years	495	8.9	93.3	8.7
12 years	803	10.3	90.3	9.6
13-15 years	987	10.7	88.5	9.3
16 years	1,460	12.1	85.5	10.5
More than 16 years	1,571	11.2	81.3	9.8
Employment characteristics				
Unemployed	751	11.4	96.0	11.2
Out of labor force	1,125	12.9	89.8	11.3
Self-employed	1,142	10.5	77.0	8.4
Paid on hourly basis	842	10.6	90.8	9.5
Union member/covered	914	9.5	85.9	9.0
Has work limitations	736	9.9	86.1	9.4
Military Veteran	866	9.8	83.9	8.8
Industries				
Postal System	1,153	8.6	85.8	8.3
Earth/Clay/Stone	809	8.8	89.4	9.1
Electrical Engineering	1,118	9.1	85.5	8.4
Synthetics	900	9.2	90.2	8.6
Mechanical Engineering	1,060	9.3	87.4	9.0
Iron/Steel	837	9.4	89.4	9.2
Mining	1,045	9.4	87.4	8.8
Education/Sports	967	9.5	85.5	9.4
Volunteer/Church	782	9.6	85.1	9.2
Wholesale Trade	1,033	9.7	87.8	9.0
Chemicals	1,229	9.7	86.5	9.3
Construction Related	835	9.7	87.1	9.2
Energy/Water	1,062	9.8	81.1	8.3
Clothing/Textiles	757	9.9	87.2	9.0
Train System	956	9.9	88.7	9.5
Other Transportation	884	10.2	88.5	9.4
Personal Services/Recr.	914	10.4	89.2	9.8
Public Administration	1,080	10.4	88.5	9.6
Construction	906	10.5	86.9	9.6
Agriculture & Forestry	861	10.5	84.0	8.9
Wood/Paper/Print	845	10.7	88.0	9.9
Food Industry	892	10.7	88.6	10.2
Retail Trade	886	10.8	89.5	10.3
Bus/Prof Services	1,072	11.0	87.8	10.1
Insurance	1,398	11.0	85.0	10.2
Health Services	1,313	11.2	86.7	10.3
Legal Services	1,319	11.4	81.4	9.8
Financial Institutions	1,704	11.7	86.0	10.6
Restaurants	679	11.9	95.2	11.6
Other/Unknown Industry	1,046	13.4	99.1	13.7

	EV / 1,000	$100\cdot c^2$	$100\cdot\theta$	$100\cdot c^2\cdot\theta$
Birth cohorts				
Before 1946	697	8.4	52.9	6.9
1946-1952	1,048	10.3	66.8	6.5
1953-1959	1,052	10.6	81.0	7.1
1960 and later	1,158	12.7	95.2	11.3
Race				
Other	980	9.4	83.0	8.4
Hispanic	862	10.2	92.8	9.4
Black	707	10.3	94.5	10.1
White	1,146	10.7	84.1	9.5
Asian/Pacific Islander	1,227	10.8	82.0	8.6
Native American	847	10.8	90.3	10.4
Job tenure				
Less than 2 years	1,022	11.0	91.3	10.4
2-5 years	1,044	10.7	88.6	10.1
5 plus years	911	9.1	81.4	8.3
Unknown	1,006	11.8	90.2	9.4
Occupations				
Transportation & Material Moving	711	9.1	91.5	9.0
Production	780	9.5	89.1	9.1
Education, Training, & Library	1,101	9.6	84.3	9.7
Building/ Grounds Cleaning & Maint.	477	9.8	93.5	9.9
Construction/Extraction/Repair/Etc.	765	9.9	91.3	9.7
Farming, Fishing, & Forestry	841	9.9	85.4	8.8
Healthcare Support	952	10.0	90.7	10.2
Protective Service	982	10.1	91.9	9.9
Computer & Mathematical	1,441	10.1	87.3	9.5
Community/Social Services	766	10.1	87.3	9.5
Business & Financial Operations	1,474	10.3	77.6	9.1
Management	1,282	10.6	78.5	8.8
Office & Administrative Support	950	10.8	86.8	9.9
Food Preparation & Serving Related	788	11.0	94.4	11.0
Sales & Related	1,322	11.0	84.8	9.9
Architecture & Engineering	1,463	11.1	83.9	10.0
Legal	2,208	11.3	75.6	9.4
Personal Care & Service	817	11.5	90.8	11.0
Arts/Design/Entert./Sports/Media	1,119	11.7	87.1	10.6
Life, Physical, & Social Science	1,413	12.1	80.9	10.3
Healthcare Practitioners & Tech.	2,620	12.3	76.5	10.0
Military Specific	1,261	13.2	94.6	12.3
Other/Unknown	1,060	13.5	98.5	13.2
Mean earnings percentile, prev. 5 years				
0 to 20	548	10.8	94.3	10.3
20 to 40	694	10.3	91.8	10.0
40 to 60	880	10.1	88.1	9.6
60 to 80	1,108	10.1	85.7	9.4
80 to 100	1,644	10.5	79.4	9.1
No reported earnings in prev. 5 yrs.	1,202	13.4	94.9	12.7

Mean share of statistic due to:	EV	Var V
Expected log-earnings profile	0.82	-
Risk of permanent shocks	0.09	0.87
Risk of temporary shocks	0.09	0.13

Note: As throughout the paper, θ is the share of men's expected remaining lifetime budget that is due to earnings (i.e., subject to earnings risk). Sample sizes are 134,552 for the first two statistics, but only 29,353 for the latter two because they use household wealth data that begins in the 1999 wave of the PSID; those statistics are computed only for household heads. Racial groups, industries, and occupations are listed in increasing order of mean estimated c^2.

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Table 5: Correlations between Estimated Lifetime Earnings Risk (c^2) and Several Measures of Annual Risk

A. Correlations with c^2

	$E[u^2 \mid X]$	$E[\Omega(t,t+2)^2 \mid X]$	Estimated $\sigma^2_{\nu it}$	Estimated $\sigma^2_{\eta it}$
Whole sample	0.25	0.28	0.29	0.52
Age range				
Up to 25	0.26	0.20	0.29	0.55
26-35	0.08	0.13	0.13	0.71
36-45	0.20	0.20	0.15	0.74
46-55	0.43	0.37	0.24	0.70
56 and above	0.52	0.46	0.56	0.51

B. Correlations with θc^2

	$E[u^2 \mid X]$	$E[\Omega(t,t+2)^2 \mid X]$	Estimated $\sigma^2_{\nu it}$	Estimated $\sigma^2_{\eta it}$
Whole sample	-0.03	0.10	0.11	0.26
Age range				
Up to 25	0.22	0.01	0.07	0.68
26-35	0.06	0.02	0.00	0.61
36-45	0.06	0.05	0.03	0.43
46-55	0.17	0.16	0.14	0.18
56 and above	0.33	0.32	0.34	0.16

Note: Each of the alternatives is an estimate of risk of annual earnings shocks: predicted squared residuals from the annual earnings regressions, predicted squared residual biennial earnings growth, and the estimated risks of annual temporary and permanent earnings shocks, respectively. Only household heads are used in Panel B because wealth data are reported at the household level.

Table 6: Estimated Elasticities of Income and Risk Variables on Four Choices

Exp. Var.	Est. Elast.	SE	P	Est. Elast.	SE	P	Est. Elast.	SE	P	Est. Elast.	SE	P	Est. Elast.	SE	P
A. Hazard ratio, transition to first household headship (N=23,126)															
EV	0.23	0.08	0.01	0.29	0.09	0.00							0.33	0.09	0.00
y(t)							0.16	0.06	0.00	0.24	0.06	0.00	0.02	0.07	0.76
c^2				-4.17	0.42	0.00							-4.15	0.52	0.00
$\sigma_\eta^2(t+1)$										-1.13	0.16	0.00	-0.63	0.19	0.00
$\sigma_v^2(t+1)$										0.29	0.07	0.00	0.34	0.07	0.00
log L	-2,054			-2,020			-2,054			-2,035			-2,010		
B. Hazard ratio, transition to first marriage (N=26,578)															
EV	0.32	0.08	0.00	0.44	0.08	0.00							0.38	0.09	0.00
y(t)							0.34	0.06	0.00	0.30	0.07	0.00	0.05	0.07	0.46
c^2				-3.24	0.37	0.00							-2.59	0.41	0.00
$\sigma_\eta^2(t+1)$										-0.73	0.13	0.00	-0.43	0.14	0.00
$\sigma_v^2(t+1)$										-0.11	0.07	0.12	-0.14	0.08	0.07
log L	-2,971			-2,938			-2,963			-2,951			-2,932		
C. Pr[Buys house between t and t+2 | Non-homeowner at t] (N=45,909)															
EV	0.89	0.04	0.00	0.91	0.04	0.00							0.80	0.04	0.00
y(t)							0.35	0.02	0.00	0.31	0.02	0.00	0.13	0.02	0.00
c^2				-1.11	0.11	0.00							-1.24	0.13	0.00
$\sigma_\eta^2(t+1)$										0.06	0.04	0.19	0.33	0.06	0.00
$\sigma_v^2(t+1)$										-0.35	0.04	0.00	-0.38	0.04	0.00
log L	-17,845			-17,774			-18,065			-18,000			-17,644		
D. Value of new house at t+2 | non-homeowner at t, homeowner at t+2 (N=6,527)															
EV	0.56	0.02	0.00	0.57	0.02	0.00							0.47	0.02	0.00
y(t)							0.27	0.01	0.00	0.27	0.01	0.00	0.12	0.01	0.00
c^2				-0.26	0.04	0.00							-0.27	0.07	0.00
$\sigma_\eta^2(t+1)$										0.16	0.03	0.00	0.14	0.05	0.00
$\sigma_v^2(t+1)$										-0.03	0.02	0.04	-0.03	0.01	0.03
R^2	0.432			0.434			0.393			0.396			0.444		

Notes: The first two panels report mean marginal elasticities of hazard rates estimated from Cox proportional hazards models with separate baseline hazards for the 32 race-cohort-education groups and standard errors clustered at the individual level; to avoid complications of time-varying independent variables with potentially lagged effects, these specifications use mean values over the at-risk period. Panel C reports mean marginal elasticities from a probit with random effects, and those in Panel D are from least-squares regressions with standard errors clustered by years. (Estimating models C and D jointly using men's prior headship status as an instrument in the probit equation reveals no statistically significant selection.) All samples include only men eligible to make the relevant transition and exclude men with no earnings in year t. Other explanatory variables include dummies for years, Census divisions, demographics (groups, race, age, SEO sample), and employment status at the year t survey (unemployed, nonparticipant, student).

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Figure 1: Mean EV and c^2, by Occupations

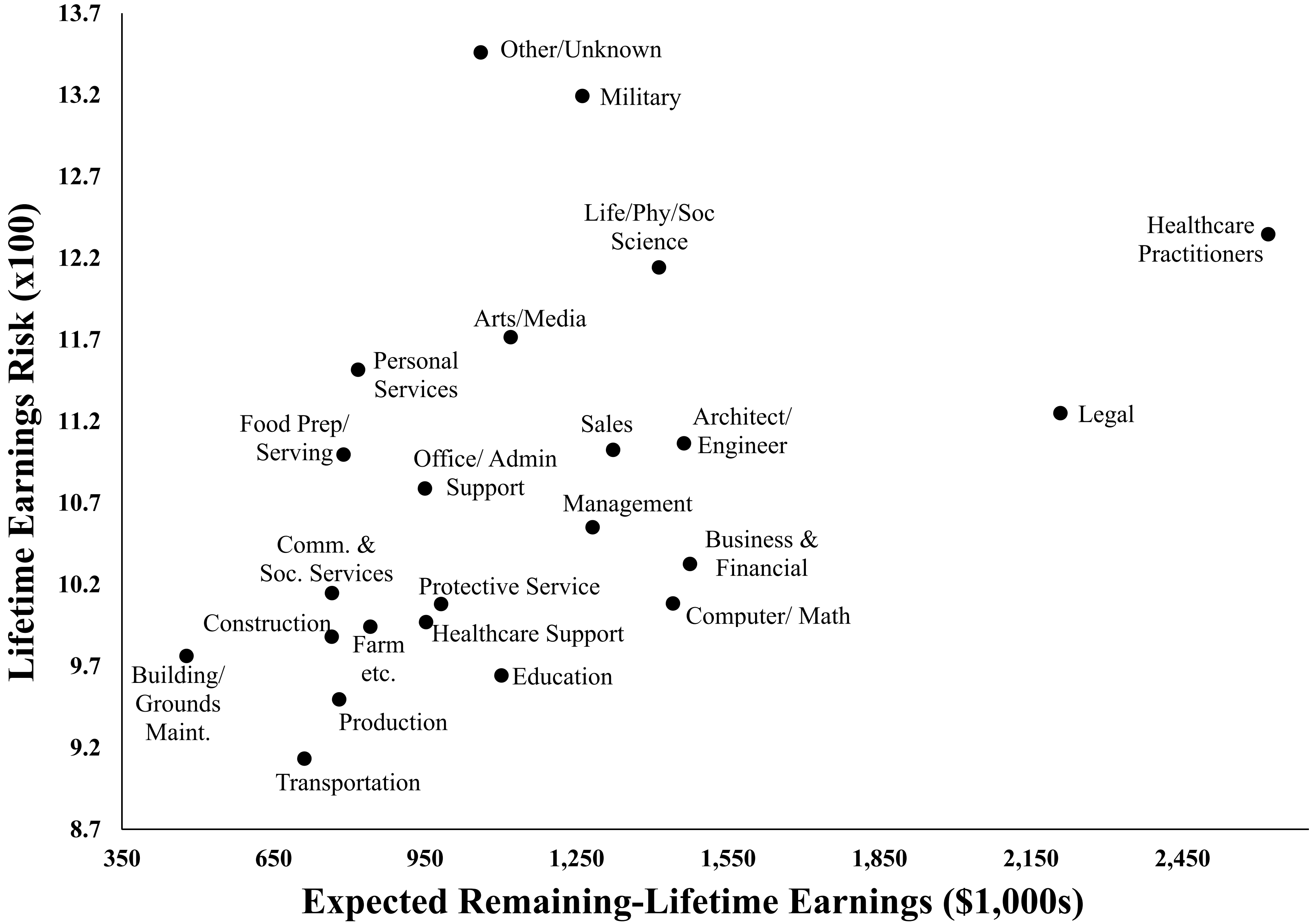

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Figure 2: Mean Estimates of c^2 by Education, 1970-2013

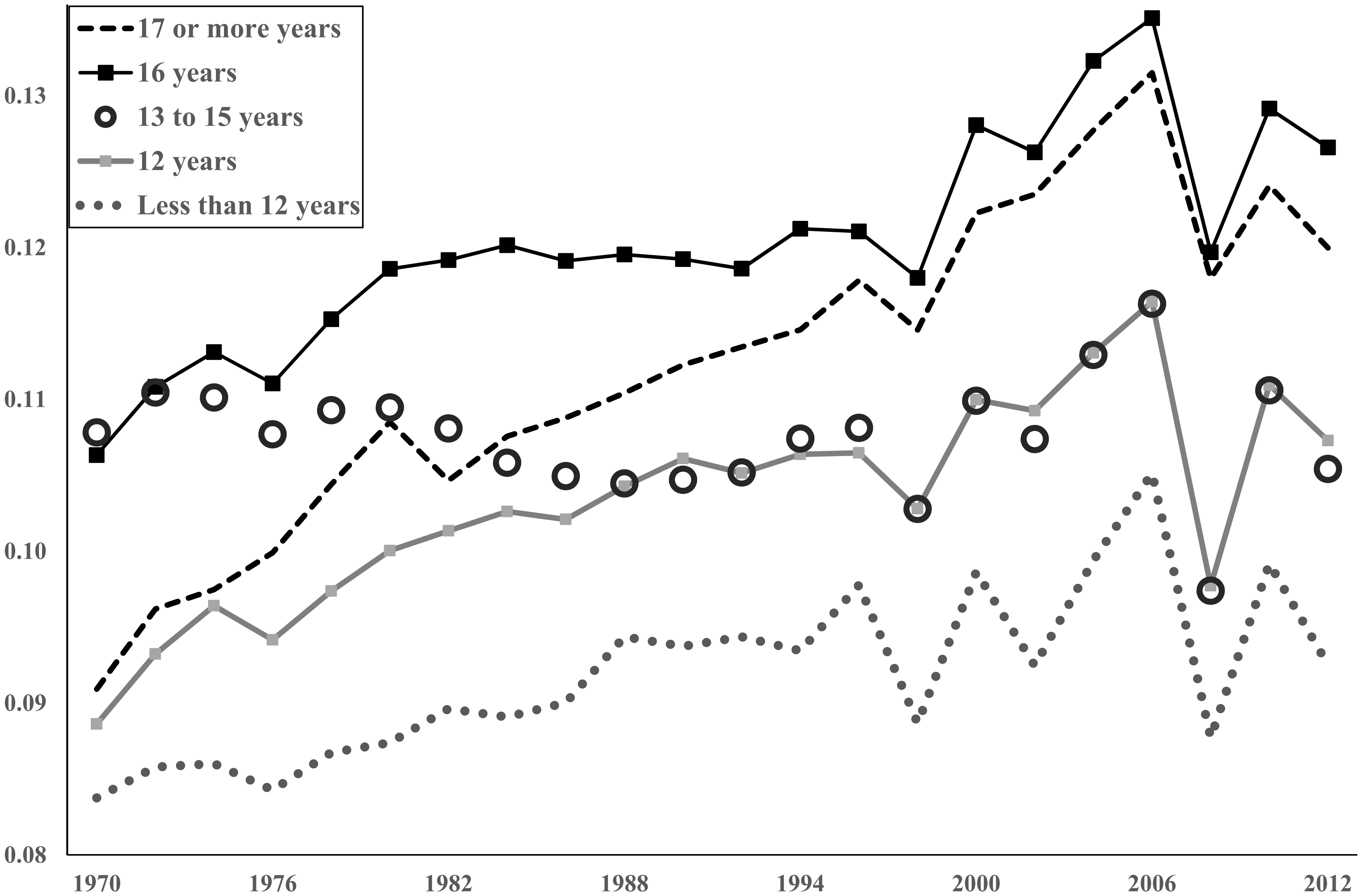

Figure 3: Expected Present Value of Remaining Lifetime Earnings (EV/1,000), Its Squared Coefficient of Variation (c^2), and Total Exposure to Lifetime Earnings Risk (θc^2), by Age, 1999-2013

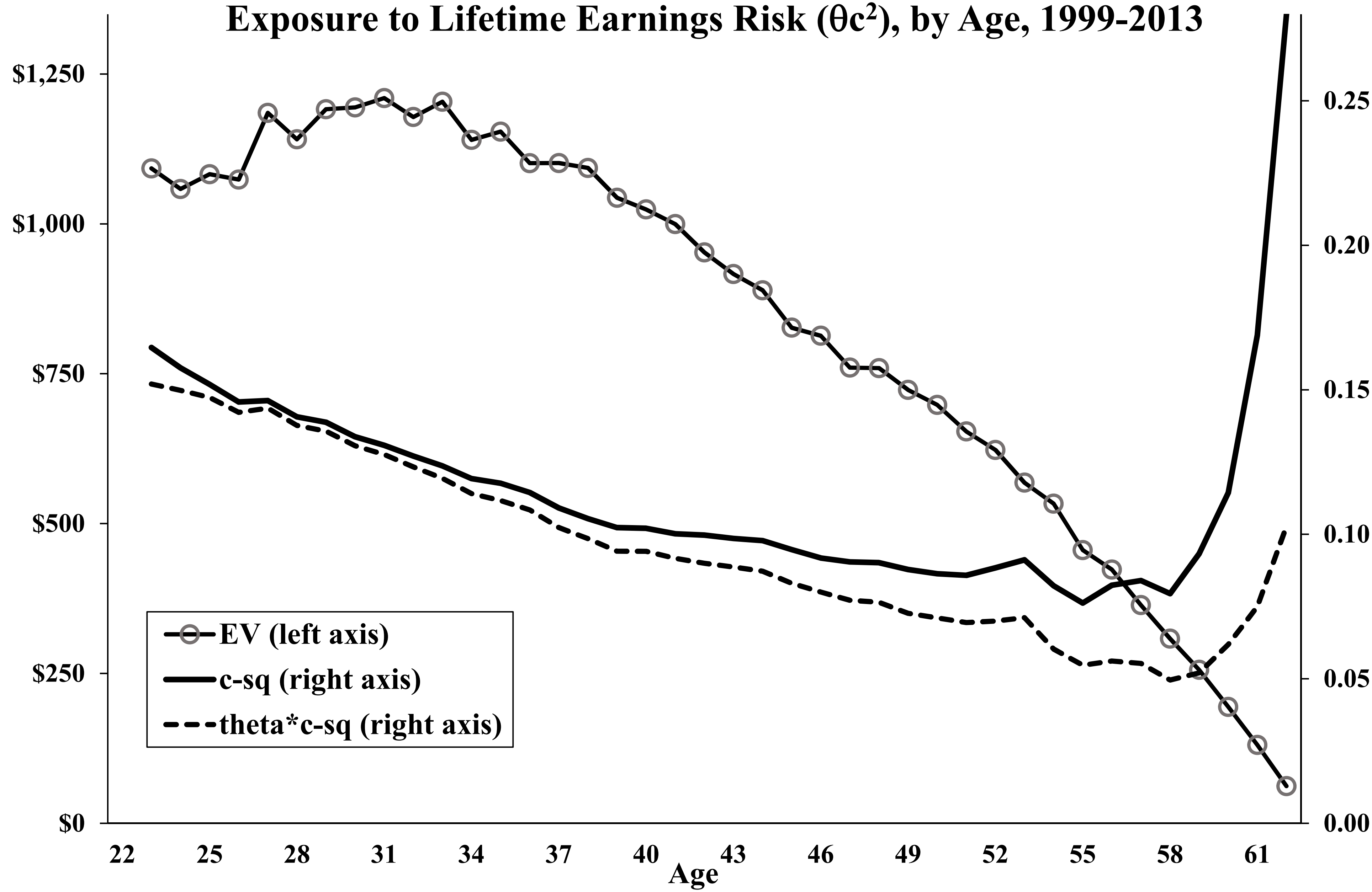

Figure 4: Mean Estimated c^2, by Age and Birth Cohort